Increasing EV Integration with Reinforcement Learning and Distribution Network Reconfiguration

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***Abstract*—The rapid increase in penetration of electric vehicles demands the widespread installation of fast charging stations. These stations require a very high level of electrical power, drastically changing the electrical load profile by increasing its peak. This results in increased system losses and voltage drops throughout the network and limits the number of electric vehicles that can charge at the same time. This paper presents a reinforcement learning-based optimization of vehicle charging location. This novel approach uses optimal distribution network reconfiguration to train an electric vehicle charging coordinator, implemented as a reinforcement learning agent.**

I. Introduction

The increasing popularity of electric vehicles (EVs) requires a sufficient charging infrastructure. However, the integration of EVs into the power grid poses challenges in managing the distribution network to maintain the balance of voltage and demand. Modern EVs use 150-300 kW in fast charge mode, 124-248 times more than average household power usage. The existing power system lacks the capacity to handle the increasing number of high-power EV loads.

One promising approach to support increased integration of EVs is to optimize their charging location. To this end, Ye et al. [1] develop a centralized allocation and decentralized execution reinforcement learning (RL) framework to maximize the profit of the charging station. The centralized allocation process assigns the EVs to either waiting or charging spots. In the decentralized execution process, individual chargers make their own charging/discharging decisions. Shin et al. [2] proposed a new multiagent deep RL method to calculate the scheduling solutions of multiple EV charging stations with a solar photovoltaic system and energy storage system, in a distributed manner, while handling dynamic runtime data. To jointly control the entire set of electric vehicles at once and find the optimal charging policy, Sadeghianpourhamami et al. [3] proposed a new Markov decision process (MDP) formulation in the RL framework, which is also scalable. Liang et al. [4] maximize the welfare of a large-scale shared EV fleet operator using deep RL combined with binary linear programming. The aforementioned studies ignore the constraints of the distribution system and focus mainly on the EV driver or charging station perspectives of the charging problem. An adaptive decentralized control algorithm for EVs is presented by Zishan et al. [5]. It relies on congestion signals generated by sensors deployed across the network. This model uses multi-agent RL where each charging point is an independent agent that learns control parameters using an off-policy actor-critic deep RL algorithm. The main drawback of this method is that it ignores the ability of the distribution system to perform reconfiguration and increase its EV capacity while controlling the voltage.

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This study presents a deep RL-based model for EV drivers to determine optimal charging locations while considering distribution network reconfiguration (DNR). The proposed model supports drivers in selecting charging spots and enhances the power grid's capacity to accommodate more EVs.

II. Experimental Setup and Results

This paper proposes a deep RL-based model to find the optimal location to charge the EV considering DNR. The overall framework of the proposed method for EV charging coordination is illustrated in Fig. 1. The EV charging coordinator first receives the DNR and system load information from the distribution system operator (DSO), the charging power data from the EVs, and the location of the charging station plus their availability data from the charging station operators. Then, based on this information, it determines the best charging station for each EV to reduce system loss, meet voltage constraints, and increase the number of EVs that can fast charge at the same time. In this context, the EV charging coordinator is referred to as the agent, and two RL algorithms named deep Q-learning (DQN) and dueling DQN (DDQN) are used to train it. It should be noted that in this study, the DSO performs optimal DNR using a pre-trained DSO agent.

In this paper, the ultimate goal of finding an optimal EV charging location is to minimize total line losses and to control the voltage limit so that more EVs can charge simultaneously. Therefore, the reward function is defined as

$$\mathcal{R}(s_t, a_t) = -C^l p_t^l(s_{t+1}) - C^v(s_{t+1}). \qquad (1)$$

In this equation, the first term represents the total line losses of the system $p_t^l(s_{t+1})$ in state s_{t+1} multiplied by a penalty term C^l with units of [1/kW]. The second term, $C^v(s_{t+1})$, is a penalty for violating the system's voltage

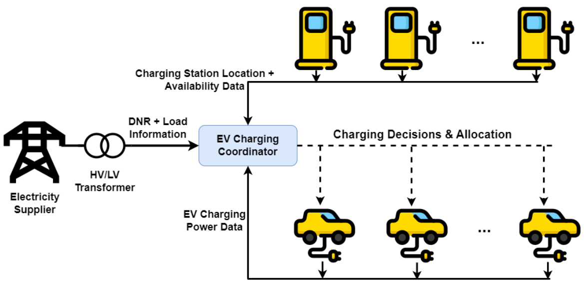

Fig. 1. System Architecture

constraints. After training, the agent learns the value of each action in a given state. Therefore, in each state, charging stations can be ranked from the most suitable to the least, based on the action value. At this point, the capacity and availability of each charging station are checked. If a station is not available, or it does not have enough capacity, the agent is not allowed to choose it.

The lower and upper voltage bounds are assumed to be 0.93 p.u. and 1.07 p.u., respectively, in the 33-bus system, and 0.95 p.u. and 1.05 p.u. in the 136-bus system. The parameter C^l in (1) is set to 10,000 and C^v to 1,000,000 $\times$ voltage deviation. The charging station locations for the IEEE 33- and 136-bus systems are considered at buses [7, 20, 25, 33] and buses [74, 96, 98, 115 ,117, 135], respectively. The moving average of mean daily rewards for 33- and 136-bus systems are depicted in Fig. 2 and Fig. 3, respectively. They have an increasing trend, indicating successful agent training.

To investigate the effectiveness of the proposed method, the following three case studies were performed:

- Case 1: The distribution system does not perform DNR and the EV charging station selection is random;
- Case 2: The distribution system performs DNR and the EV charging station selection is random;
- Case 3: The distribution system performs DNR and the EV charging station selection is optimized with RL.

Figure 4 compares the number of EVs that can charge at the same time for the three cases. Additionally, the minimum voltage values are given in Table I. When DNR is not used, no EV can charge due to voltage drop in both the 33-bus and 136-bus systems. For the 33-bus system, training the agent with the DQN algorithm yields an increase in the number of EVs that can charge simultaneously from 3 to 5. However, the DDQN algorithm is not successful in assigning charging locations to EVs. This can be attributed to the fact that the DNR strategies found by DDQN are suboptimal. Similarly,

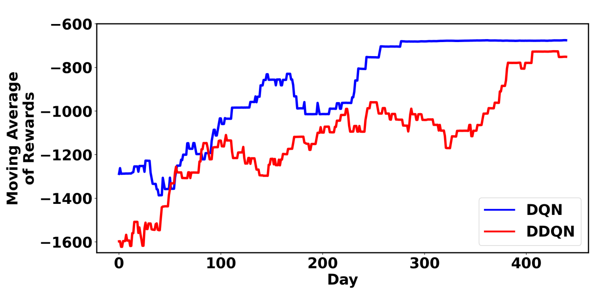

Fig. 2. 60-step moving average of mean daily rewards for 33-node system

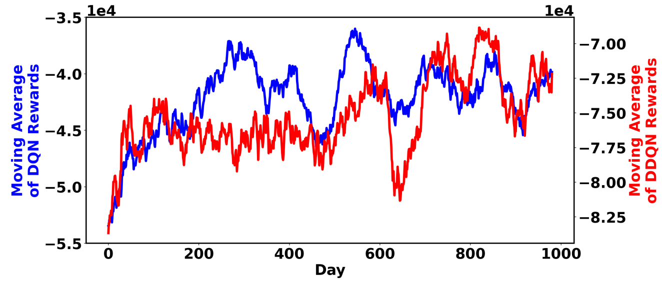

Fig. 3. 60-step moving average of mean daily rewards for 136-node system

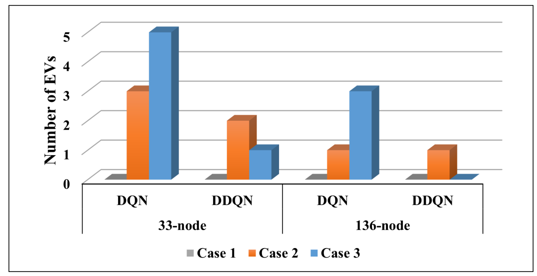

Fig. 4. Number of EVs integrated in Cases 1-3

TABLE I
SYSTEM VOLTAGES IN CASES 1-3

Algorithm	Test System			
	33-node		136-node	
	DQN	DDQN	DQN	DDQN
Case 1	0.910	0.910	0.915	0.915
Case 2	0.934	0.940	0.950	0.951
Case 3	0.936	0.935	0.950	0.948

the DQN algorithm performs well in the 136-node system and increases the number of EVs that can be simultaneously charged from 1 to 3, while the DDQN algorithm does not properly train the EV charging coordinator.

III. CONCLUSION

A reinforcement learning-based algorithm was proposed to optimize the selection of charging stations for EVs considering DNR to increase simultaneous fast charging. Using DQN, the charging coordinators improved the integration of EVs by at least 66.67% for the 33- and 136-bus systems compared to random charging locations. However, the DDQN algorithm did not perform well.

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